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Real-time prediction of dynamic irregularity and acceleration of HSR bridges using modified LSGAN and in-service train

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Abstract. Dynamic irregularity and acceleration of bridges subjected to high-speed trains provide crucial information for comprehensive evaluation of the health state of under-track structures. This paper proposes a novel approach for real-time estimation of vertical track dynamic irregularity and bridge acceleration using deep generative adversarial network (GAN) and vibration data from in-service train. The vehicle-body and bogie acceleration responses are correlated with the two target variables by modeling train-bridge interaction (TBI) through least squares generative adversarial network (LSGAN). To realize supervised learning required in the present task, the conventional LSGAN is modified by implementing new loss function and linear activation function. The proposed approach can offer pointwise and accurate estimates of track dynamic irregularity and bridge acceleration, allowing frequent inspection of high-speed railway (HSR) bridges in an economical way. Thanks to its applicability in scenarios of high noise level and critical resonance condition, the proposed approach has a promising prospect in engineering applications.

Keywords: bridge acceleration; high-speed railway (HSR); least squares generative adversarial network (LSGAN); real-time prediction; train-bridge interaction (TBI); track dynamic irregularity

1. Introduction

High-speed railways have been recognized as one of the modern transportation means with multiple merits. Bridges serve as the crucial infrastructure to sustain high-speed trains, allowing a smooth running of the vehicles. Furthermore, bridges usually account for a large portion of the high-speed rail mileage, of which the vast majority are short and medium span girder bridges constructed with standardized design, fabrication, and erection (He *et al*. 2017). In light of this, the bridge condition greatly affects safe operation of HSR network. Considering HSR stretching hundreds or thousands of kilometers, efficient monitoring of the bridge state can facilitate timely and optimized maintenance schedule.

Track irregularities, reflecting the random rail imperfection and structural deformation, are regarded as the main self-excitation of TBI system (Montenegro *et al*. 2021). High levels of irregularity pose threats to both the running safety and stability of passing trains, and accelerate the degradation of bridge structures due to the resultant excessive vibrations (Zhai *et al*. 2013). Therefore, track irregularities serve as a critical index adopted in the evaluation and maintenance of HSR. It is of great significance to promptly collect the irregularity data and further to detect changes in track geometry. Moreover, structural dynamic response can be utilized as an indication of bridge condition. In particular, bridge accelerations provide basic data for structural frequency or damping derivation, dynamic safety evaluation, and damage detection, among others (Kim *et al*. 2017, Meixedo *et al*. 2021, Azim and Gül 2020). These responses have been accurately computed using the train-bridge coupled dynamics (Yang *et al*. 2004, Xia *et al*. 2018, Salcher and Adam 2015, Peixer *et al*. 2021), despite that sophisticated TBI model and time-consuming computation process are generally required.

Track recording vehicle, where accelerometers, gyroscopes, laser, camera and so on are mounted (Weston *et al*. 2007), refers to one of the main tools nowadays to inspect track irregularity represented by dynamic displacement of the wheel (Bocciolone *et al*. 2007). Thus, dynamic irregularity is regarded as the superposition of random rail irregularity and bridge deformation due to the dynamic loading of track recording vehicle, at the time-varying wheel location. The inertial reference method has been implemented to identify track irregularities (Lee *et al*. 2012), which has the shortcoming of unrealistic trend drift due to double integration of the acceleration. Furthermore, the use of track recording vehicle usually causes high cost

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and interference to scheduled high-speed train operations (Guo *et al*. 2021), which reduce the frequency of track inspection. As a result, track deterioration may not be timely recognized, leading to safety risk for HSR. To overcome the abovementioned drawbacks, some researchers resorted to alternative methods based on dynamic responses of in-service vehicle and inverse analysis (Tsunashima *et al*. 2014, Czop *et al*. 2011, Alfi and Bruni 2008, Real *et al*. 2011, Thiyagarajan *et al*. 2021, Cantero and Basu 2015, OBrien *et al*. 2017, Wei *et al*. 2016). However, these contributions only focused on the subgrade section, in which the presented algorithms are inapplicable for the bridge section due to the effects of train-bridge dynamic interaction (Wang *et al*. 2021). Recently, Xiao *et al*. (2020) adopted Kalman filter algorithm to detect track irregularity of bridges using vehicle-body accelerations resulting from a simplified two degrees-of-freedom vehicle model. The employed vehicle model may produce different results than the actual train vehicles by ignoring vibrations of the bogie and effects of the suspension systems. Generally, inverse analysis algorithms are model-based methods, of which the estimation accuracies depend heavily on the reliability of vehicle models. According to Thiyagarajan *et al*. (2021), the inverse analysis solution may be inaccurate and unstable. When a sophisticated vehicle model is selected, the associated derivation becomes quite complicated and difficult. Challenges related to the nature of the algorithm can also arise. For example, since Kalman filtering is a linear filter, it may encounter difficulties while handling the nonlinear relationships between vehicle dynamic response and track irregularity.

On the other hand, more and more research attentions have been paid to the application of artificial neural network algorithms in low-cost estimation related to bridge dynamic behaviors. Owing to their superior abilities including nonlinear mapping and fitting, robustness to large noise, quick prediction, and so on, neural networks have been employed to develop data-driven models for structural excitation or response prediction in fast or real-time manner. For instance, ground motion and wind speed were forecast using various types of neural networks (Amiri *et al*. 2012, Vahedian *et al*. 2022, Lim *et al*. 2022, Yu *et al*. 2018, Gou *et al*. 2021). With the known seismic or wind excitation, surrogate models of the structural system were established to yield dynamic response with much less computational time compared to conventional physical models (Soleimani and Liu 2022, Rachedi *et al*. 2021, Onat and Gul 2018, Xue and Ou 2021, Abbas *et al*. 2020, Fang *et al*. 2020, Wang *et al*. 2022). Nevertheless, very few attempts have been made to introduce emerging neural network algorithms into train-bridge coupled dynamics. Deep learning predictive models fed with track irregularity were newly presented to replace time-consuming coupling dynamic simulation and to estimate TBI system response (Li *et al*. 2021, 2022, 2023a, b).

As a new achievement in the field of deep learning, GAN has attracted increasing interest since it was developed by Goodfellow *et al*. (2014). GAN is one class of unsupervised learning algorithms comprised of two models, i.e., generator (denoted as *G*) and discriminator (denoted as *D*) which compete against each other to improve one another's performance in the meanwhile. Because of the superior ability of learning both the low- and high-frequency features in the data, GAN and its variants such as conditional GAN (Mirza and Osindero 2014), Wasserstein GAN (Arjovsky *et al*. 2017), and LSGAN (Mao *et al*. 2017) were adopted to establish data-driven methods for structural dynamic load or response reconstruction (Fan *et al*. 2021, Lei *et al*. 2021, Xiong and Chen 2021, Yu *et al*. 2021), damage identification (Soleimani-Babakamali *et al*. 2022, Zhang *et al*. 2020, Xu and Liu 2022, Shim *et al*. 2022, Liu *et al*. 2022), data augmentation (Gao *et al*. 2019, Maeda *et al*. 2021), and structural design (Liao *et al*. 2021) in the civil engineering domain. Yuan *et al*. (2021) developed the surrogate model of a vehicle system to infer track irregularity excitation using Wasserstein GAN. Nonetheless, their investigation concentrated on track irregularity estimation associated with the subgrade section.

In this work, aiming to facilitate efficient condition monitoring, a novel approach is proposed for real-time pointwise prediction of dynamic irregularity and acceleration of HSR bridges using LSGAN and in-service train data. The estimates become available as vehicle response data are being recorded. A modified LSGAN-based surrogate model of high-speed train-bridge system is developed for the first time, leveraging the adversarial training strategy of GAN to obtain a low-cost surrogate that can well capture TBI in the real world. Moreover, the widely adopted GAN is modified by defining new loss functions to accommodate the pointwise prediction, which means that irregularity and acceleration can be forecast at discrete spatial and temporal intervals respectively. Accordingly, the proposed modified LSGAN turns into a supervised learning model contrary to the unsupervised learning one used in the conventional GANs. The proposed approach, employing the vehicle-body and bogie acceleration data from few sensors mounted on the in-service trains as the input, allows real-time estimates of track dynamic irregularity containing structural deformation and bridge acceleration response. Therefore, a large amount of bridges along HSR lines can be inspected in a timely and economical manner.

The rest of the paper is organized as follows. The proposed methodology is first overviewed in Section 2. Subsequently, the modified LSGAN-based predictive model is elaborated in Section 3. A case study is performed in Section 4 to demonstrate the efficacy of the proposed approach applied to typical HSR bridge. Several significant factors including train speed, data noise, and sensor quantity are also examined. Finally, main conclusions of the present work are summarized in Section 5.

2. Overview of the proposed methodology

The proposed approach is sketched in Fig. 1, which consists of four modules, namely, data collection, model construction, model use, and condition evaluation. Each module can be described as follows.

Data collection: The pre-collected data include vehicle-

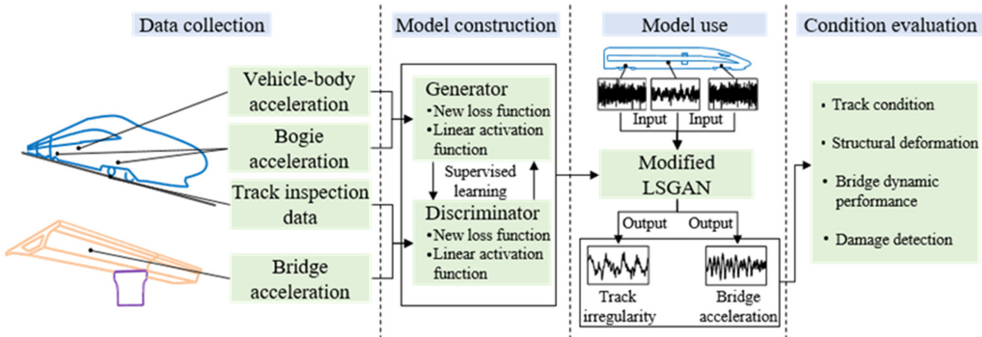


Fig. 1 Framework of the proposed methodology

body and bogie accelerations, track inspection data, and bridge acceleration. The track dynamic irregularity can be obtained from the regular inspection performed with track recording vehicle or comprehensive inspection car serving in high-speed railways. The vehicle and bridge acceleration data can be collected through ordinary accelerometers. It should be noted that despite hundreds or thousands of kilometers of the high-speed rail, data collection can be stopped once sufficient data for training deep learning models have been in hand.

Model construction: This study employs LSGAN to achieve real-time estimation of vertical dynamic irregularity and acceleration of HSR bridges. The vertical track irregularities have a great influence on dynamic effects of both the vehicle and bridge including train running safety and stability, and bridge vibrations. Moreover, the estimated dynamic irregularities contain the deformation of under-track structure due to train loading and other effects, which can assist in comprehensive evaluation of bridge health state. Specifically, through a critic network (i.e., discriminator) and adversarial training, the data produced by the generator become more and more similar to the real ones. However, the regular LSGAN trained in an unsupervised way is not suitable for the present task since labeled training data, with input and output being the vehicle response and track dynamic irregularity or bridge acceleration, call for a supervised learning strategy. To this end, a modified LSGAN is developed herein with critical changes made to the loss function and output layer of both generator and discriminator. To ensure an accurate pointwise prediction, a multi-layer gate recurrent unit (GRU) neural network and a convolutional neural network (CNN) autoencoder are proposed for creating the generator. Additionally, fully connected feedforward neural network (FFNN) is utilized to construct the discriminator.

Model use: The proposed modified LSGAN is trained in advance before it is put into use. The well-trained predictive model is fed with the unseen vehicle acceleration data measured on in-service trains. To localize the track and bridge that require further evaluation based on the estimates, it is necessary to obtain the train position information, which can be provided by positioning techniques such as GPS. In the present methodology, only three sets of acceleration response collected at the vehicle-body and two bogies are needed to perform the prediction. Subsequently, dynamic irregularity and acceleration of the bridge can be estimated simultaneously.

Condition evaluation: The obtained track dynamic irregularity can be used to carry out a preliminary but rapid assessment of the track condition. Furthermore, the vertical deformation of under-track structure can also be extracted by data processing with respect to the estimated irregularity (Matsuoka and Tanaka 2023), which provides vital information about the health state of HSR bridges. On the other hand, the predicted bridge accelerations enable an evaluation of structural dynamic behavior in both time- and frequency-domain, as well as structural damage detection.

3. Modified LSGAN-based predictive model

The cornerstone of the proposed approach is based on the modified LSGAN. Such a deep learning predictive model will be elaborated in this section.

3.1 Modified LSGAN

GAN belongs to a type of deep generative models, of which the basic form is illustrated in Fig. 2. The generator can produce data $\tilde{\mathbf{x}}$ when fed with a random noise $\mathbf{z}$. As a binary classifier, the role of the discriminator is to judge the similarity between the two sets of input data, i.e., generated data $\tilde{\mathbf{x}}$ and target data $\mathbf{x}$. Hence, G and D compete with one another to better play their respective role. The training objective of GAN can be given in the form of cross entropy as

$$\begin{aligned}&\min_G \max_D V(D,G)\\&= E_{\mathbf{x}\sim p(\mathbf{x})}(\log D(\mathbf{x})) + E_{\mathbf{z}\sim p(\mathbf{z})}\Big(\log\Big(1-D\big(G(\mathbf{z})\big)\Big)\Big)\end{aligned} \tag{1}$$

where $V(D, G)$ is the training objective of GAN; $p(\mathbf{x})$ and $p(\mathbf{z})$ are the probability distributions of the target data $\mathbf{x}$ and noise $\mathbf{z}$; and $E(\ )$ is the expectation function.

Eq. (1) shows that the training of GAN consists of two separate training tasks associated with the generator and discriminator. When gradient-based optimization algorithms are employed, the generator and discriminator can be updated by descending and ascending their stochastic gradients, $g_{\boldsymbol{\theta}_G}$ and $g_{\boldsymbol{\theta}_D}$, expressed as

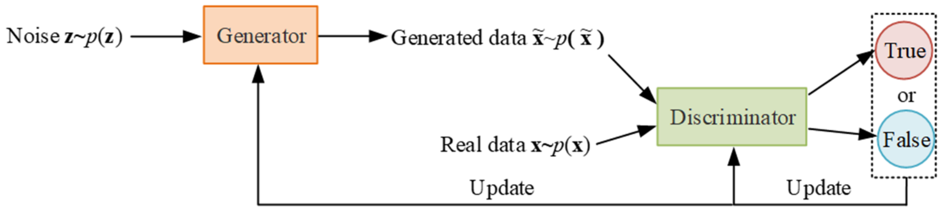


Fig. 2 Basic architecture of GAN

$$g_{\boldsymbol{\theta}_G} = \nabla_{\boldsymbol{\theta}_G}\left(\frac{1}{M_B}\sum_{i=1}^{M_B}\log\left(1-D(G(\mathbf{z}^i))\right)\right) \tag{2a}$$

$$g_{\boldsymbol{\theta}_D} = \nabla_{\boldsymbol{\theta}_D}\left(\frac{1}{M_B}\sum_{i=1}^{M_B}\log\left(D(\mathbf{x}^i)\right) + \frac{1}{M_B}\sum_{i=1}^{M_B}log\left(1-D\left(G(\mathbf{z}^i)\right)\right)\right) \tag{2b}$$

where M_B is the number of samples in a mini-batch; and $\boldsymbol{\theta}_G$ and $\boldsymbol{\theta}_D$ are the parameters of the generator and discriminator.

The use of cross entropy function may cause the issue of vanishing gradients in the updates of generator when fake samples are on the correct side of the decision boundary. Therefore, the LSGAN is developed (Mao *et al.* 2017), which adopts mean square error (*MSE*) function as the loss function. The training objective of LSGAN can be expressed as

$$\min_G V(G) = \frac{1}{2}E_{\mathbf{z}\sim p(\mathbf{z})}(D(G(\mathbf{z}))-c)^2 \tag{3a}$$

$$\min_D V(G) = \frac{1}{2}E_{\mathbf{x}\sim p(\mathbf{x})}(D(\mathbf{x})-b)^2 + \frac{1}{2}E_{\mathbf{z}\sim p(\mathbf{z})}(D(\mathbf{z})-a)^2 \tag{3b}$$

where a and b are the label values for the fake and real output; and c denotes the value that the generator wants the discriminator to believe for fake data.

In this study, a supervised learning method is required since the input of the predictive model is vehicle dynamic response which constitutes the data pair with track dynamic irregularity or bridge acceleration. However, regular GAN and LSGAN are considered as unsupervised learning models with random noise being the input. To overcome the abovementioned limitation, a modified LSGAN is proposed herein. Firstly, the label values a, c, and b in the objective functions of D and G (Eq. (3)) are replaced by the Euclidean distance between the generated and target data, and zero respectively. Secondly, an *MSE* loss is added to the training objective of G (Eq. (3a)). Finally, the activation function of the output layer in D is changed to a linear function which makes D a function fitter rather than a binary classifier. These modifications enable LSGAN to produce continuous values instead of two discrete numbers for binary classification and to avoid the problem of vanishing gradient. Therefore, the modified LSGAN performs well in both training and prediction, suitable for accomplishing the task in the present work.

The training process of the modified LSGAN can be characterized as

$$\min_G V(G) = \frac{1}{2}E_{\mathbf{z}\sim p(\mathbf{z})}(\|G(\mathbf{z})-\mathbf{x}\|_2)^2 + \frac{1}{2}E_{\mathbf{z}\sim p(\mathbf{z})}\left(D\left(G(\mathbf{z})\right)-\|G(\mathbf{z})-\mathbf{x}\|_2\right)^2 \tag{4a}$$

$$\min_D V(G) = \frac{1}{2}E_{\mathbf{x}\sim p(\mathbf{x})}\left(D(\mathbf{x})\right)^2 + \frac{1}{2}E_{\mathbf{z}\sim p(\mathbf{z})}(D(G(\mathbf{z}))-\|G(\mathbf{z})-\mathbf{x}\|_2)^2 \tag{4b}$$

Accordingly, G and D can be updated by descending their stochastic gradients expressed as

$$g_{\boldsymbol{\theta}_G} = \nabla_{\boldsymbol{\theta}_G}\left(\frac{1}{2M_B}\sum_{i=1}^{M_B}\left(\left\|G(\mathbf{z}^i)-\mathbf{x}^i\right\|_2\right)^2 + \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D\left(G(\mathbf{z}^i)\right)-\left\|G(\mathbf{z}^i)-\mathbf{x}^i\right\|_2\right)^2\right) \tag{5a}$$

$$g_{\boldsymbol{\theta}_D} = \nabla_{\boldsymbol{\theta}_D}\left(\frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D(\mathbf{x}^i)\right)^2 + \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D\left(G(\mathbf{z}^i)\right)-\left\|G(\mathbf{z}^i)-\mathbf{x}^i\right\|_2\right)^2\right) \tag{5b}$$

3.2 The architecture of the generator model

To generate reliable track dynamic irregularity and bridge acceleration data, two architectures of G are designed using multi-layer GRU neural network and CNN autoencoder respectively. Fig. 3 shows that the multi-layer GRU network consists of fully connected (FC) layer, batch normalization (BN) layer, and GRU layer. Vehicle dynamic response data are treated first with a FC layer to be prepared for the following GRU layers. After each FC or GRU layer, a BN layer is implemented to normalize the output and to speed up the training process.

The GRU cell shown in Fig. 4 plays a core role in the GRU layer, which can be described as

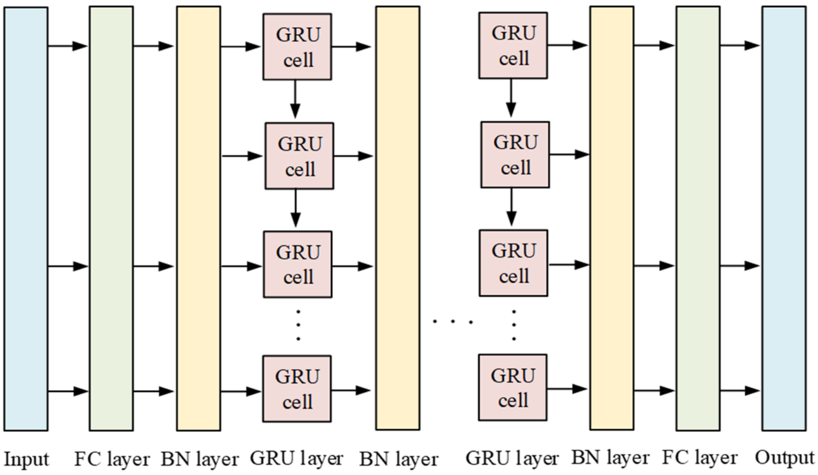


Fig. 3 The architecture of the generator for track dynamic irregularity estimation (Generator T)

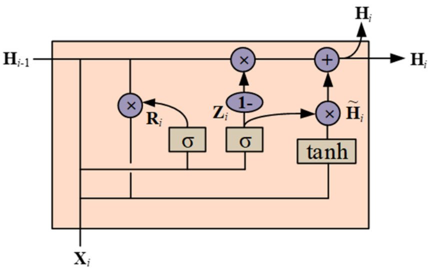


Fig. 4 The detail of GRU cell

$$\boldsymbol{R}_i = \sigma(\mathbf{W}_R[\mathbf{H}_{i-1}, \mathbf{X}_i]) \tag{6a}$$

$$\mathbf{Z}_i = \sigma(\mathbf{W}_Z[\mathbf{H}_{i-1}, \mathbf{X}_i]) \tag{6b}$$

$$\widetilde{\mathbf{H}}_i = tanh(\mathbf{W}_{\widetilde{H}}[\mathbf{H}_{i-1} \bullet \mathbf{R}_i, \mathbf{X}_i]) \tag{6c}$$

$$\mathbf{H}_i = (1 - \mathbf{Z}_i) \bullet \mathbf{H}_{i-1} + \mathbf{Z}_i \bullet \widetilde{\mathbf{H}}_i \tag{6d}$$

where $\mathbf{H}_i$ and $\mathbf{H}_{i-1}$ are the cell state at the present and previous time instants; $\widetilde{\mathbf{H}}_i$ is a transition matrix; $\mathbf{X}_i$ is the input of the cell; $\mathbf{W}_R$, $\mathbf{W}_Z$, and $\mathbf{W}_{\widetilde{H}}$ are the inner weight matrices; and • is the symbol of Hadamard product.

On the other hand, the CNN autoencoder model for bridge acceleration estimation (see Fig. 5) is composed of convolutional (Conv.) layer, BN layer, max pooling (MP) layer, and upsampling (US) layer. In the encoder part, Conv. layers aim to extract the features of vehicle dynamic response, which are subsequently compressed through MP layers. The coding of vehicle accelerations is input into the decoder part to generate bridge acceleration data with the convolutional and upsampling (i.e., nearest neighbor unpooling) operations.

3.3 The architecture of the discriminator model

The authenticity of the generated track dynamic irregularity or bridge acceleration data is examined by the discriminator model, which herein is constructed with fully connected FFNN composed of FC layer and BN layer as shown in Fig. 6. Each FC layer is followed by a BN layer. As mentioned previously, linear activation function is utilized in the output layer. The output of D is supposed to be zero and the degree of differences between the generated and target data when the real and fake data are input respectively.

3.4 Training algorithm

The training of the modified LSGAN, described as a supervised learning procedure, is shown in Algorithm 1. During the training process, the collected vehicle acceleration data are fed into the generator, and therefore, the generator is trained first and parameters of the discriminator are frozen meanwhile. Track dynamic irregularity and bridge acceleration produced by the generator and their measured counterparts serve as the input of the discriminator. Subsequently, the training of the

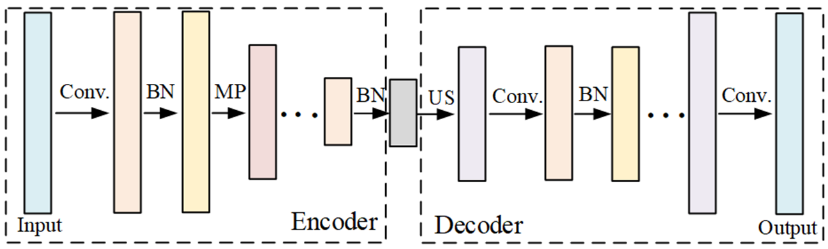


Fig. 5 The architecture of the generator for bridge acceleration prediction (Generator A)

Algorithm 1. Train the modified LSGAN

Input: Vehicle acceleration $\left((\ddot{\mathbf{X}}_v)^1, (\ddot{\mathbf{X}}_v)^2, \ldots (\ddot{\mathbf{X}}_v)^M\right)$; //$M$ is the number of training samples
Dynamic irregularity $\left((\mathbf{I}_t)^1, (\mathbf{I}_t)^2, \ldots (\mathbf{I}_t)^M\right)$ or bridge acceleration $\left((\ddot{\mathbf{X}}_b)^1, (\ddot{\mathbf{X}}_b)^2, \ldots (\ddot{\mathbf{X}}_b)^M\right)$;

Output: Trained modified LSGAN;

Initialize parameters of the generator and discriminator;
Divide the training samples into m mini-batches with the size of M_B;
For $j = 1$ to n_{epoch}: //n_{epoch} is the number of total training epochs
For $h = 1$ to m:
Generate track dynamic irregularity $\left((\tilde{\mathbf{I}}_t)^1, (\tilde{\mathbf{I}}_t)^2, \ldots (\tilde{\mathbf{I}}_t)^{M_B}\right)$ or bridge acceleration $\left((\tilde{\ddot{\mathbf{X}}}_b)^1, (\tilde{\ddot{\mathbf{X}}}_b)^2, \cdots (\tilde{\ddot{\mathbf{X}}}_b)^{M_B}\right)$ by the generator;
Calculate the loss function of the generator as

$$Loss_G = \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(\left\|G\left((\ddot{\mathbf{X}}_v)^i\right) - \mathbf{Y}^i\right\|_2\right)^2 + \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D\left(G\left((\ddot{\mathbf{X}}_v)^i\right)\right) - \left\|G\left((\ddot{\mathbf{X}}_v)^i\right) - \mathbf{Y}^i\right\|_2\right)^2$$

where $\mathbf{Y}^i = (\mathbf{I}_t)^i$ or $(\ddot{\mathbf{X}}_b)^i$;
Calculate the gradient of the generator by backpropagation;
Update parameters of the generator by gradient descent;
Freeze the generator's parameters and calculate the loss function of the discriminator as

$$Loss_D = \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D\left((\ddot{\mathbf{X}}_v)^i\right)\right)^2 + \frac{1}{2M_B}\sum_{i=1}^{M_B}\left(D\left(G\left((\ddot{\mathbf{X}}_v)^i\right)\right) - \left\|G\left((\ddot{\mathbf{X}}_v)^i\right) - \mathbf{Y}^i\right\|_2\right)^2$$

Calculate the gradient of the discriminator by backpropagation;
Update parameters of the discriminator by gradient descent;
Endfor
Endfor
Return Trained modified LSGAN

discriminator is performed while parameters of the generator remain unchanged. As such, the modified LSGAN is updated and optimized gradually with the loss getting smaller and smaller, by alternately training the generator and discriminator.

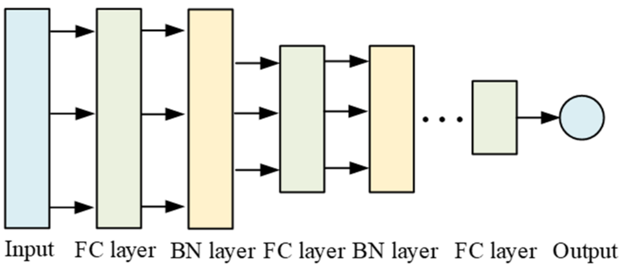


Fig. 6 The architecture of the discriminator for dynamic irregularity or acceleration estimation (Discriminator T or A)

4. Application to the 32 m box girder bridge

The proposed approach is illustrated on the simply-supported 32 m box girder bridge traversed by a primary type of high-speed train used in China, which approximately occupies 95% of the China's HSR bridge inventory (see Fig. 7). Standardized design drawing, manufacturing process, and erection method have been adopted to ensure consistent construction quality of the bridges. For illustration purposes, bridge accelerations are assumed herein to be measured at the bridge mid-span for both training and prediction processes, although acceleration estimation would not be restricted by the measurement location.

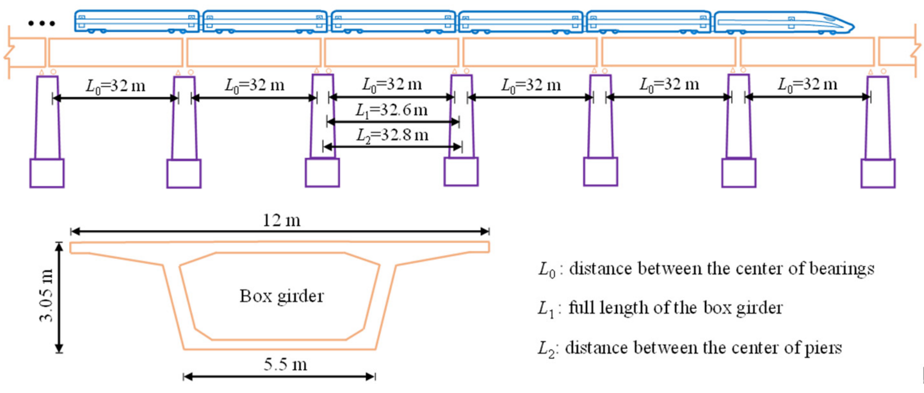


Fig. 7 The 32 m box girder bridge traversed by high-speed train

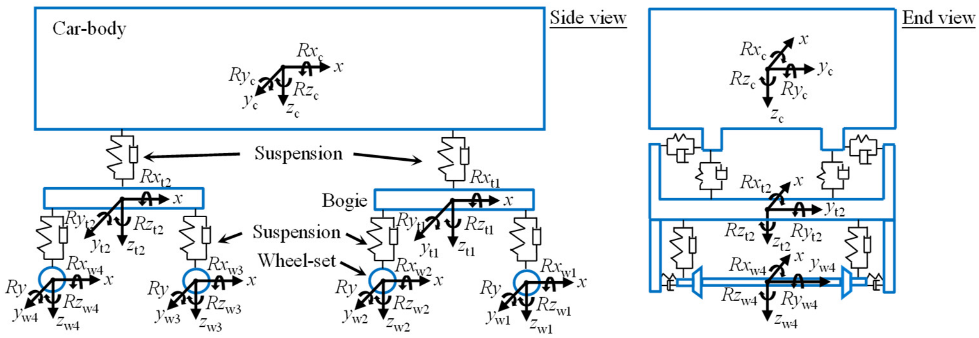


Fig. 8 The three-dimensional dynamic model of HSR vehicle

4.1 Training data creation using train-bridge coupled dynamics

The data sets required for training the proposed modified LSGAN model are obtained from dynamic analyses of coupled train-bridge system. In particular, a three-dimensional TBI model, composed of vehicle model, bridge model, and wheel-rail contact model, is established to realize the dynamic simulation. Through the complete vehicle model in the three-dimensional coupled system model, the rolling motion of the vehicle which has a significant effect on vertical vibrations of the train and bridge can be taken into account.

The high-speed train vehicle is herein regarded as a multi-rigid-body dynamic system as shown in Fig. 8. The rigid-bodies are one vehicle-body, two bogies, and four wheel-sets respectively. Rigid-body movements in five different directions are considered for vehicle-body or bogie, namely, sway (y), floating (z), rolling (Rx), pitching (Ry), and yawing (Rz). In addition, the degrees-of-freedom associated with each wheel-set are y, z, Rx, and Rz. Between the vehicle-body, bogie, and wheel-set are the suspension systems which can be modeled as springs and dashpots with certain stiffness and damping. The equation of motion of the vehicle subsystem is deduced from the Lagrange's equation. The bridge model is built using finite elements. Consequently, the dynamic equation of the TBI system can be expressed as

$$\begin{cases}\mathbf{M}_v\ddot{\mathbf{X}}_v + \mathbf{C}_v\dot{\mathbf{X}}_v + \mathbf{K}_v\mathbf{X}_v = \mathbf{F}_v \\ \mathbf{M}_b\ddot{\mathbf{X}}_b + \mathbf{C}_b\dot{\mathbf{X}}_b + \mathbf{K}_b\mathbf{X}_b = \mathbf{F}_b\end{cases} \tag{7}$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are the mass, damping, and stiffness matrices; $\ddot{\mathbf{X}}$, $\dot{\mathbf{X}}$, and $\mathbf{X}$ are the acceleration, velocity, and displacement; $\mathbf{F}$ is the force vector; and v and b denote the vehicle and bridge respectively.

The determination of dynamic interactive forces requires using the wheel-rail contact model. In the vertical direction, the movement of wheel-set equals the superposition of random irregularity on the steel rail and deformation of the bridge structure. Based on this compatibility, the vertical force component in vectors $\mathbf{F}_v$ and $\mathbf{F}_b$ can be identified. Moreover, the Kalker's creep theory is employed to calculate the lateral interactive force between the wheel and rail. Since the motion of vehicle and bridge subsystems appear in both $\mathbf{F}_v$ and $\mathbf{F}_b$, a numerical iterative solution scheme has been formulated to solve Eq. (7) using Newmark-β method and in-house computation procedure (Li *et al*. 2015).

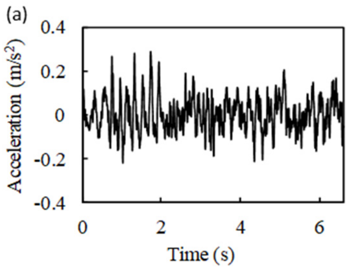
Parameters of the high-speed train can be found in Li *et al*. (2021). Additionally, to create one data block ten consecutive spans of the simply-supported box girder is modeled using beam elements. To obtain the initial condition for the TBI analysis, e.g., the vibration state of train vehicles when they arrive at the bridge, dynamic simulation of the moving train under the random excitation of track irregularity is started when the first wheel-set of the train is 50 m away from the bridge. The initial state of the bridge is assumed to be static. Considering that high-speed trains usually travel at the fixed operating speed (e.g., 300 km/h), a constant speed of 300 km/h is employed throughout the dynamic simulation. A time step size of 0.005 s is adopted in TBI analysis, which corresponds to a temporal resolution of 200 Hz for both input and output data. Furthermore, the obtained track irregularities are converted from time-domain to spatial-domain according to the train speed and time step size. Specifically, the spatial frequency can be calculated as 2.4 (1/m) which is considered sufficient to cover the wavelength range of HSR irregularity.

Random irregularities on the steel rail are generated based on the Chinese HSR track spectrum stemming from massive measurement data (NRA 2014). The power spectral density (PSD) is expressed by a piecewise power function as

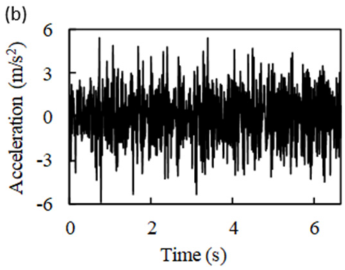
$$S(f) = \frac{A}{f^k} \tag{8}$$

where $S(\ )$ is the fitted track spectral; f is the spatial frequency; and A and k are the coefficients of which the values for each section of S are prescribed by NRA (2014).

For illustration purposes, the input and output features of the modified LSGAN associated with one of the data blocks are displayed in Figs. 9-10. It can be observed that during the train passage, vertical acceleration responses of the bogie are much larger than that of the vehicle-body. It is worthwhile noting that the irregularity data presented in Fig. 10(a) are vertical dynamic displacements of the wheel measured relative to the perfect track geometry. As mentioned previously, vertical wheel movement depends on the superposition of random irregularity and bridge deformation at the wheel location. Hence, the measured

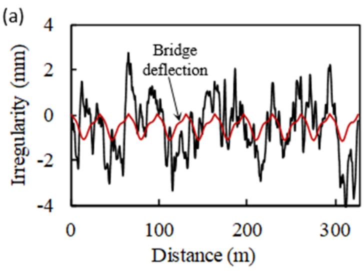


(a) Vehicle-body acceleration

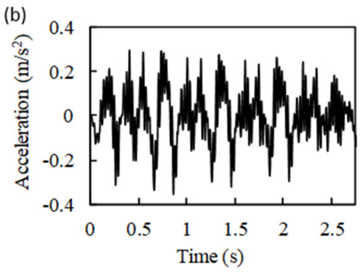


(b) Bogie acceleration

Fig. 9 Example of the input feature in the modified LSGAN



(a) Track dynamic irregularity



(b) Bridge acceleration

Fig. 10 Example of the output feature in the modified LSGAN

track irregularities embody the dynamic deflection of bridge structure (i.e., red curve in Fig. 10(a)).

4.2 Network parameters

According to the architecture proposed in Sections 3.2 and 3.3, hyperparameters of the generator and discriminator in modified LSGAN for the prediction of dynamic irregularity and acceleration of the 32 m box girder bridge is determined, as shown in Tables 1-2. For the estimation of track dynamic irregularity and bridge acceleration, vehicle acceleration data are divided according to a constant length of 78 and 546, which is equal to the number of time steps associated with one wheel-set and the entire train passing over the bridge at 300 km/h, respectively. It is found that the prediction accuracies are very close between the input data of one vehicle and the whole train, mainly due to the fact that accelerations of various vehicles in the train do not differ significantly as they pass over the bridge with the same excitation of irregularities. Thus, vertical accelerations of the vehicle-body and two bogies at the first car are herein employed, which is favorable for the implementation of the approach and development of a lightweight predictive model. Accordingly, the input dimensions become 78×3 and 546×3. In addition, Generator T consists of 3 GRU layers, 2 FC layers, and 4 BN layers while Generator A contains 4 Conv. layers, 4 BN layers, and 3 MP layers in the encoder part, and 4 Conv. layers, 3 BN layers, and 4 US layers in the decoder part. Discriminator T and Discriminator A are constructed using fully connected FFNN with 5 FC layers and 4 BN layers, and 6 FC layers and 5 BN layers respectively.

Table 1 Details of the modified LSGAN model for track dynamic irregularity estimation

Generator T					Discriminator T			
Layer name	Input size	Output size	Kernel size	Activation function	Layer name	Input size	Output size	Activation function
FC_1	78×3	78×48	/	tanh	FC_1	78×1	40×1	tanh
BN_1	78×48	78×48	/	/	BN_1	40×1	40×1	/
GRU_1	78×48	78×48	48×48	/	FC_2	40×1	20×1	tanh
BN_2	78×48	78×48	/	/	BN_2	20×1	20×1	/
GRU_2	78×48	78×48	48×48	/	FC_3	20×1	10×1	tanh
BN_3	78×48	78×48	/	/	BN_3	10×1	10×1	/
GRU_3	78×48	78×48	48×48	/	FC_4	10×1	5×1	tanh
BN_4	78×48	78×48	/	/	BN_4	5×1	5×1	/
FC_2	78×48	78×1	/	linear	FC_5	5×1	1×1	linear

Table 2 Details of the modified LSGAN model for bridge acceleration estimation

Generator A						Discriminator A			
Layer name	Input size	Output size	Kernel size	Stride	Activation function	Layer name	Input size	Output size	Activation function
Conv._1+BN_1	546×3	272×32	4×3×32	2	ReLU	FC_1	546×1	400×1	tanh
MP_1	272×32	136×32	/	2	/	BN_1	400×1	400×1	/
Conv._2+BN_2	136×32	67×64	4×32×64	2	ReLU	FC_2	400×1	200×1	tanh
MP_2	67×64	33×64	/	2	/	BN_2	200×1	200×1	/
Conv._3+BN_3	33×64	15×128	4×64×128	2	ReLU	FC_3	200×1	100×1	tanh
MP_3	15×128	7×128	/	2	/	BN_3	100×1	100×1	/
Conv._4+BN_4	7×128	2×256	4×128×256	2	ReLU	FC_4	100×1	50×1	tanh
US_1	2×256	10×256	5	/	/	BN_4	50×1	50×1	
Conv._5+BN_5	10×256	7×128	4×256×128	1	ReLU	FC_5	50×1	25×1	tanh
US_2	7×128	35×128	5	/	/	BN_5	25×1	25×1	/
Conv._6+BN_6	35×128	25×64	11×128×64	1	ReLU	FC_6	25×1	1×1	linear
US_3	25×64	100×64	4	/	/				
Conv._7+BN_7	100×64	96×32	5×64×32	1	ReLU				
US_4	96×32	576×32	6	/	/				
Conv._8	576×32	546×1	31×32×1	1	ReLU				

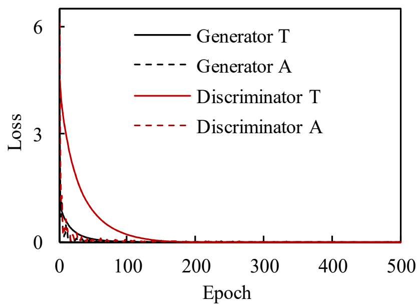


Fig. 11 Training loss of the modified LSGAN

Data sets from 1000 and 300 bridge spans are utilized for the dynamic irregularity and acceleration estimation respectively. Accordingly, 130 samples of track irregularity are randomly generated based on its PSD shown in Eq. (8). Alongside the parameters of the high-speed train and 32 m box girder considered, these irregularity samples are adopted to perform the TBI analysis under 300 km/h, with respect to ten bridge spans each time. Due to the use of different irregularity excitations, TBI analyses result in 1300 data sets significantly different from each other. When collecting the data sets through field measurements, 1000 bridge spans represent about 32 kilometers of irregularity data which merely account for a small portion of the length of HSR lines. On the other hand, due to the high train frequency in HSR lines, e.g., dozens or hundreds each day, it is also feasible to gain sufficient data associated with hundreds of train-crossing events for bridge acceleration estimation.

The obtained data sets are split into 90%, 5%, and 5% for training, validation, and test of the proposed deep learning models. Moreover, the training sets are divided into 18 mini-batches. Both the modified LSGANs are trained using adaptive gradient descent algorithm, i.e., RMSprop with an initial learning rate of 0.0001. The software and hardware platforms for the model construction and training are respectively Tensorflow 2.4.0 and a desktop computer with CPU of Intel Core i7-8700K and GPU of GTX 2060.

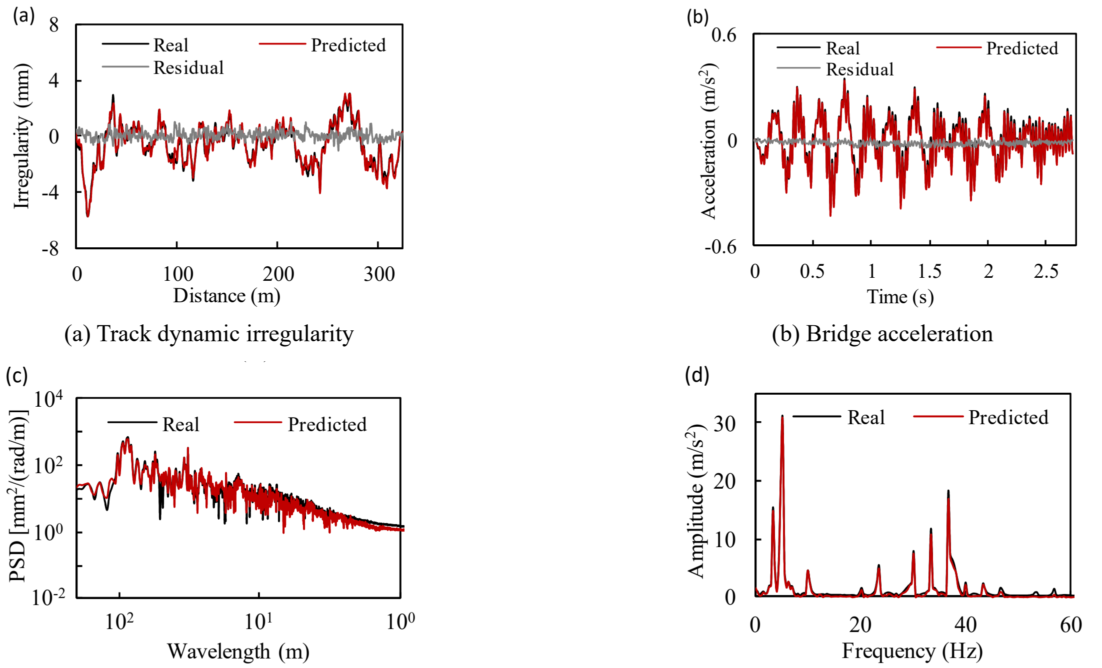
4.3 Results and discussion

The training losses of the generator and discriminator varying with the number of epoch are displayed in Fig. 11. It is observed that the training losses of Generator T, Generator A, and Discriminator A, decrease rapidly after a few epochs. Although more epochs are needed for Discriminator T to reach stable loss values, all the four models can be well trained with small losses.

Fig. 12 shows the estimation results of track dynamic irregularity and bridge acceleration under the train speed of 300 km/h, representing an operating speed in China's HSR. It can be seen from Fig. 12(a) that dynamic irregularities can be effectively inspected with small differences between the predicted and actual track longitudinal profiles. Moreover, the PSD of dynamic irregularity is calculated and compared as shown in Fig. 12(c). A good coincidence between the two sets of PSD results can also be observed. Figs. 12(b) and 12(d) demonstrate that the proposed modified LSGAN is able to provide accurate estimation of bridge acceleration responses in both time- and frequency-domain.

4.3.1 Effect of train speed

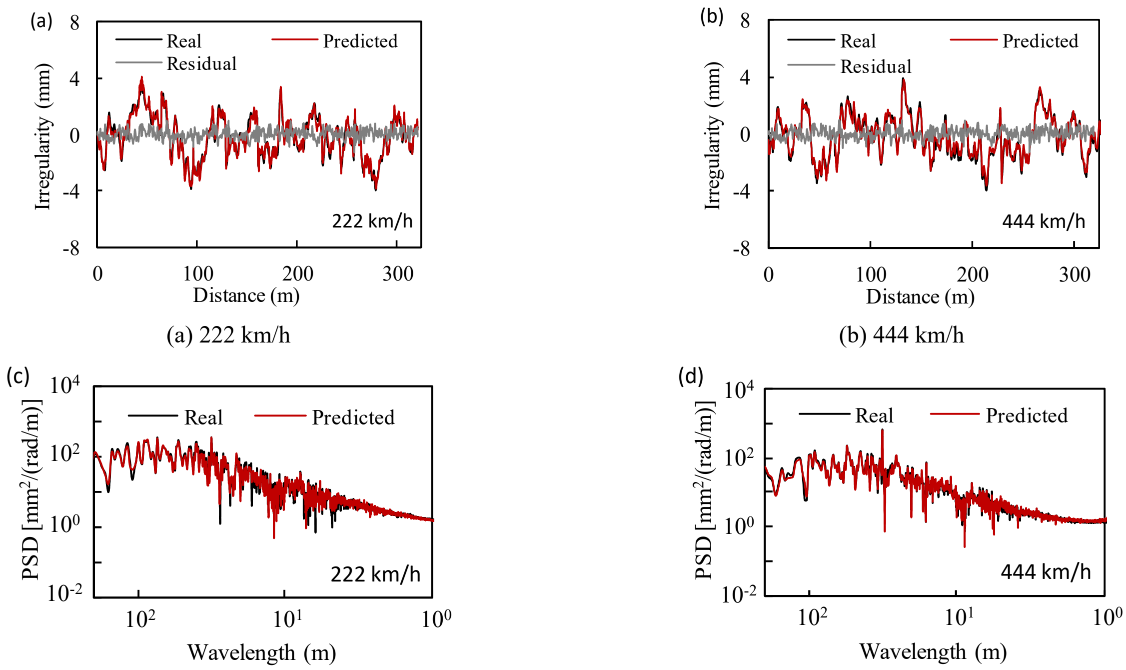
To investigate the prediction performance of the proposed approach under various train speeds, resonant conditions are examined since excessive vibrations of TBI system (e.g., displacement and acceleration) can be induced



(a) Track dynamic irregularity (b) Bridge acceleration

(c) Track dynamic irregularity (d) Bridge acceleration

Fig. 12 Estimation result and residual error under the operating speed of 300 km/h



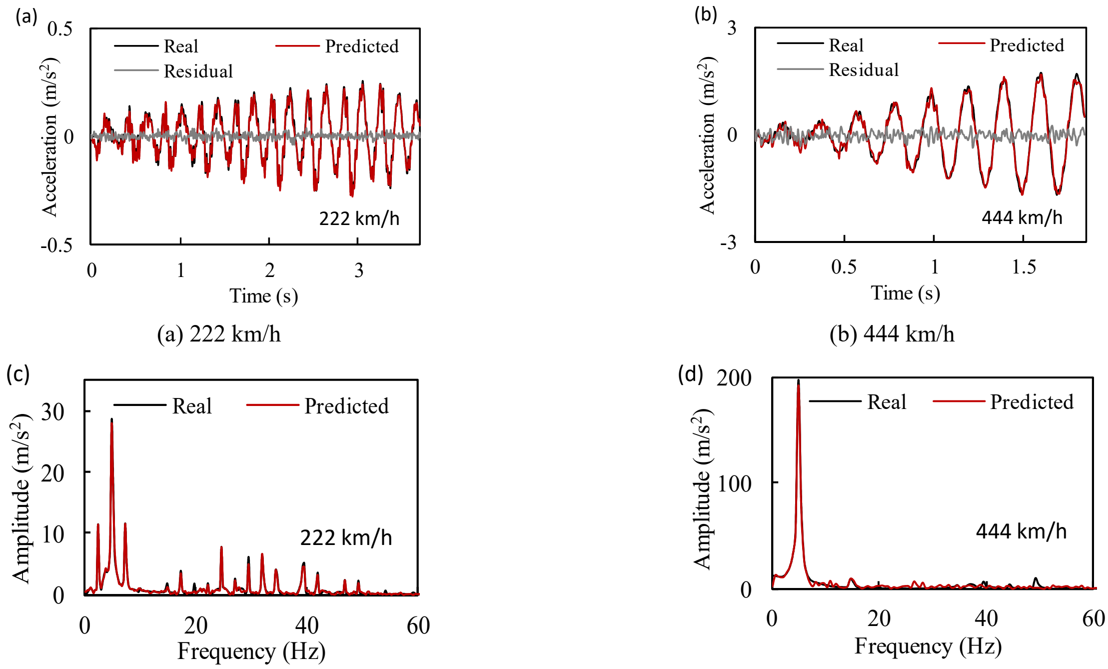
(a) 222 km/h (b) 444 km/h

(c) 222 km/h (d) 444 km/h

Fig. 13 Estimated track dynamic irregularity and its PSD under resonant train speeds

if there is a resonance phenomenon. The resonant condition will be satisfied when $V_{re} = f_b l_v / i$, where V_{re} = resonant speed, f_b = bridge natural frequency, l_v = vehicle length, and i = positive integer (Xia *et al*. 2014). The first and second critical train speeds can then be calculated as 444 km/h and 222 km/h in the present analysis. Although 444 km/h is beyond the current operating speed limit of high-speed railways, it provides an appropriate scenario to demonstrate the robustness of the proposed approach to train travel speed.

Under the resonant speed, bridge responses are gradually amplified by the passing train vehicles. It is anticipated that the bridge deflection impacts track dynamic irregularity more considerably compared to the nonresonant condition. Despite the intense structural vibration in such circumstances, one can observe from Figs. 13-14 that the



(a) 222 km/h (b) 444 km/h

(c) 222 km/h (d) 444 km/h

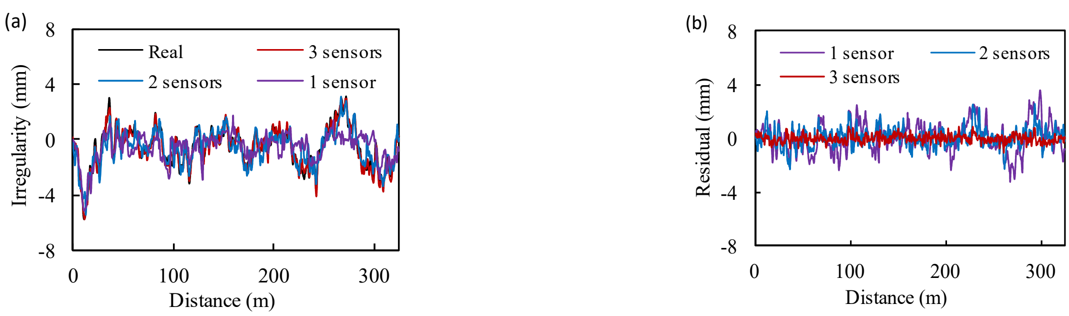
Fig. 14 Estimated bridge acceleration and its Fourier spectrum under resonant train speeds

Table 3 Summary of the metric values under typical train speeds

Metric	Track dynamic irregularity			Bridge acceleration		
	300 km/h	222 km/h	444 km/h	300 km/h	222 km/h	444 km/h
MSE	3.53e-3	5.90e-3	5.96e-3	9.17e-4	1.65e-3	1.88e-3
PVE	3.26%	4.85%	4.49%	2.35%	3.65%	4.36%
M	0.0183	0.0155	0.0369	0.0242	0.0235	0.0282
P	0.0653	0.0821	0.0646	0.0217	0.0424	0.0458
MPC	0.0678	0.0834	0.0744	0.0325	0.0485	0.0538

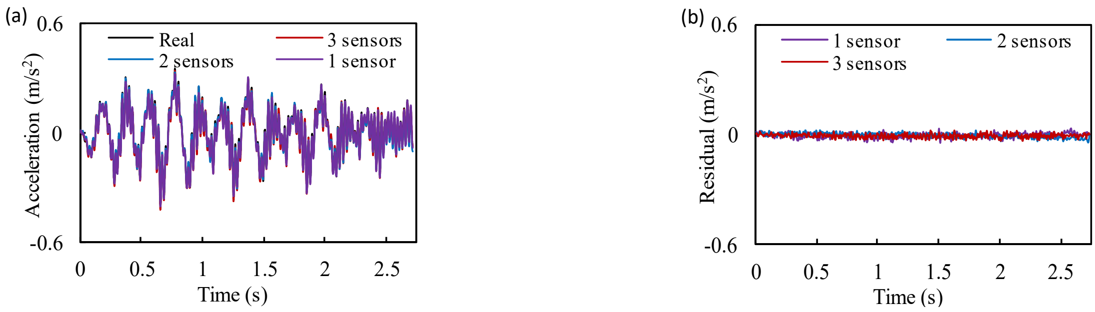
dynamic irregularity and acceleration of the bridge can be predicted in a pointwise fashion with high accuracy. In other words, the estimation performance of the present approach is hardly affected by the travel speed of in-service train.

To further investigate the prediction accuracy of the proposed approach, five metrics are employed, namely, *MSE*, peak value error (*PVE*), magnitude (*M*), phase (*P*), and magnitude-phase-composite (*MPC*). *PVE* can measure the gap between the estimated and actual maximum values which are of practical significance for both irregularity and acceleration. *M*, *P*, and *MPC* are associated with the discrepancies in the magnitude, phase, and their combination of two waves respectively (Tsunashima *et al.* 2014). It can be seen in Table 3 that while under resonant conditions the prediction accuracy generally decreases



(a) Result (b) Residual error

Fig. 15 Estimation of dynamic irregularity under different numbers of sensors

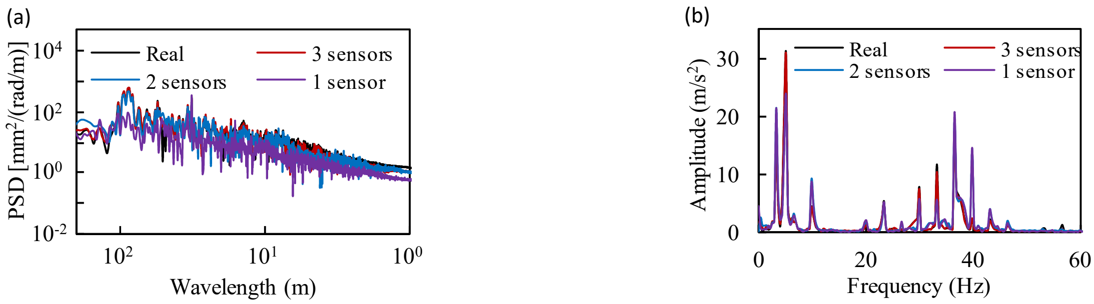


(a) Result (b) Residual error

Fig. 16 Estimation of bridge acceleration under different numbers of sensors

Table 4 Effect of the number of sensors on the estimation accuracy

Metric	Track dynamic irregularity			Bridge acceleration		
	3 sensors	2 sensors	1 sensor	3 sensors	2 sensors	1 sensor
MSE	3.53e-3	3.21e-2	1.10e-1	9.17e-4	1.47e-3	2.11e-3
PVE	3.26%	6.22%	13.17%	2.35%	3.91%	4.55%
M	0.0183	0.0251	0.1674	0.0242	0.0157	0.0153
P	0.0653	0.1295	0.2127	0.0217	0.0331	0.0362
MPC	0.0678	0.1319	0.2767	0.0325	0.0366	0.0393



(a) Track dynamic irregularity (b) Bridge acceleration

Fig. 17 Estimation results in frequency-domain under different numbers of sensors

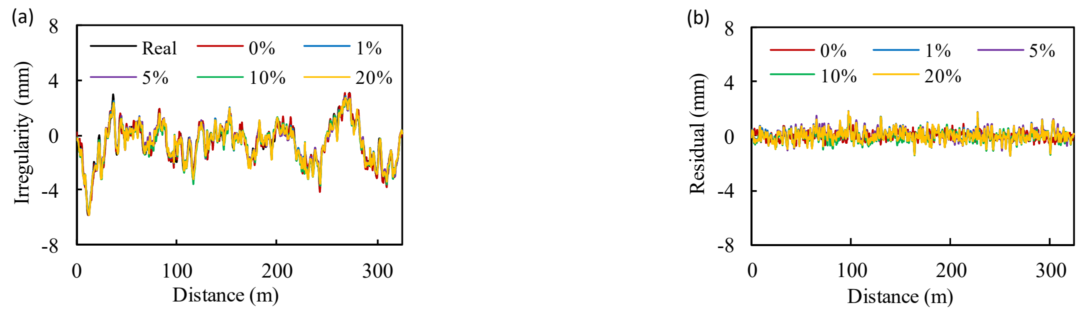
slightly, the calculated values of all the metrics remain small at three considered speeds. In particular, *PVE*s associated with dynamic irregularity and acceleration are less than 5%.

4.3.2 Effect of the number of sensors

In the present study, three accelerometers arranged on the vehicle-body and two bogies are required to collect the input data. The number of sensors is reduced herein to one or two, corresponding to the input of vehicle-body or two bogies acceleration respectively. One can observe from the comparison results displayed in Figs. 15-16 and Table 4 that the number of accelerometers has a considerable influence on the performance of the proposed approach. Overall, the prediction accuracy can be improved when accelerations at more locations are utilized. In particular, dynamic irregularity estimation is more sensitive to the sensor number compared to bridge acceleration. If only vehicle-body accelerations serve as the model input, *PVE* becomes larger than 10% which will undermine the practical value of the estimated irregularity. The abovementioned influence can also be evidenced by the comparison in frequency-domain shown in Fig. 17.

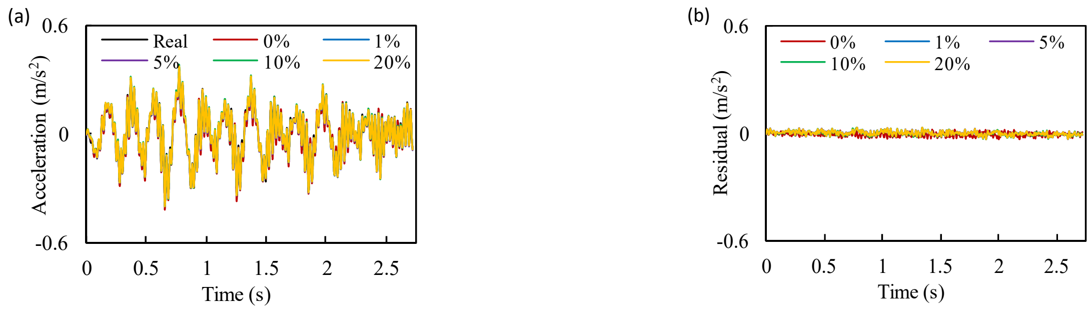
4.3.3 Effect of data noise

The collected vehicle response signal can inevitably contain noise. The white Gaussian noise is injected into the input data with four different contamination levels, i.e., 1%, 5%, 10%, and 20%, to study the prediction performance of the proposed approach. Figs. 18-19 show that despite a noise level up to 20%, prediction accuracies associated with both track dynamic irregularity and bridge acceleration are not significantly impacted. Table 5 demonstrates that with the increase in the noise level, the estimation errors slightly grow. However, the modified LSGAN can provide satisfactory prediction accuracies even under the noise level of 20%.



(a) Result (b) Residual error

Fig. 18 Estimation of dynamic irregularity under different noise levels



(a) Result (b) Residual

Fig. 19 Estimation of bridge acceleration under different noise levels

Table 5 Effect of data noise on the estimation accuracy

Metric	Track dynamic irregularity					Bridge acceleration				
	0%	1%	5%	10%	20%	0%	1%	5%	10%	20%
MSE	3.53e-3	4.89e-3	7.21e-3	8.13e-3	9.37e-3	9.17e-4	1.00e-3	1.31e-3	1.51e-3	2.01e-3
PVE	3.26%	3.75%	4.34%	5.18%	5.07%	2.35%	3.01%	3.10%	3.64%	3.84%
M	0.0183	0.0194	0.0287	0.0264	0.0273	0.0242	0.0248	0.0243	0.0238	0.0245
P	0.0653	0.0649	0.0697	0.0743	0.0757	0.0217	0.0223	0.0247	0.0267	0.0274
MPC	0.0678	0.0677	0.0754	0.0789	0.0805	0.0325	0.0334	0.0346	0.0358	0.0368

5. Conclusions

In this paper, a novel low-cost approach to real-time estimation of track dynamic irregularity and bridge acceleration of high-speed railways using modified LSGAN and vibration data from in-service train is proposed. Deep learning models are developed for the first time to build a data-driven mapping between vehicle vibration response and dynamic irregularity or acceleration of HSR bridge, making full use of the adversarial learning of generator and discriminator in GAN. To address the supervised learning task at hand, the regular GAN trained with unsupervised learning is modified by implementing new loss function and linear activation function of the output layer. Deep learning architectures of the generator and discriminator for pointwise prediction are proposed based on gate recurrent unit neural network, convolutional neural network autoencoder, and fully connected feedforward neural network.

The presented methodology is illustrated on the 32 m box girder bridge in HSR. The required training data are generated through high-fidelity simulation of the coupled train-bridge system. Low estimation errors have been observed when the train travels at both operating speed and resonant speed. Moreover, the proposed approach is robust to the input noise. A noise level up to 20% does not significantly reduce the prediction accuracies.

The proposed approach enables frequent inspection of the bridge state via real-time estimation of dynamic irregularity and acceleration using only three accelerometers mounted on the cabin and two bogies of in-service high-speed train. The estimated data provide a basis for comprehensive assessment of bridge condition. In particular, bridge deflection reflecting the deformation of under-track structure and its health state can be extracted from the obtained dynamic irregularity data. Bridge accelerations allow to compute dynamic characteristics and to perform vibration-based damage detection. Due to its robustness to the noise interference and variability in train speed, the proposed approach is suitable for engineering applications.

It is worth noting that when using the data from a new type of train for the prediction, it would be necessary to collect new data and retrain the predictive model in advance. To lessen the costs related to data collection, the reduction of required training samples would deserve future investigation. In addition, although the prediction of track irregularity focuses on the vertical direction, the presented methodology could be used to develop predictive models for the estimation of lateral irregularity, which can potentially be a research topic in the future.

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